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Proposing a Response Hierarchy Model to Explain How CS Faculty Adopt Teaching Interventions in Higher Education

Dr. Elise Deitrick, Codio

Elise has a BS in Computer Science and PhD in STEM Education. Her thesis was on interdisciplinary, collaborative computing using mixed methodologies. Elise combines her decade of teaching experience with her research background to create evidence-based computing education tools in her current role at Codio.

Mr. Joshua Ball, Codio

Vice President of Marketing at Codio

Megan McHugh, Codio

Megan McHugh has a BA in Communication and MA in Integrated Marketing Communications. With the perspective of a career centered in private sector technology and cybersecurity, she greatly values the contributions made by EdTech organizations, like Codio, to help faculty deliver better learning outcomes in CS and STEM for students of every level.

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Abstract

Despite the high volume of existing Computer Science Education research, the literature indicates that these evidence-based practices are not making their way into classrooms. While K12 faces pressures from policy and increasing opportunities through professional development to learn these best practices, Higher Education has different accelerants. This paper proposes a variant on a response hierarchy model from marketing literature to illustrate how faculty become aware of and choose to adopt pedagogical interventions. We pose a series of research questions to refine the proposed model. We investigate if the volume of research about an intervention predicts faculty awareness of it. We ask if particular experienced and perceived challenges and benefits of a given intervention affect an intervention's overall perceived level of benefit or challenge. We then look at which variables can predict intent and implementation of interventions. Finally, we considered confounding variables such as the unconscious influence of research results and demographic factors to see if there were aspects unaccounted for by the proposed model.

We collected survey data from over 100 faculty members who taught CS in the United States and ran linear regressions, ANOVAs, and Welch's t-tests, to address our wide range of research questions. Our results suggest that a simplified response hierarchy model holds explanatory power for illustrating how faculty members become aware of and choose to adopt evidence-based teaching interventions. We also found a lack of demographic confounding variables and re-produced that faculty, despite being researchers, are not swayed by education study results. By providing an evidence-based model for how faculty adopt teaching interventions, we offer new insights into how to effectively disseminate research results to increase the likelihood that the associated teaching interventions are adopted.

Introduction

Computing education research constantly develops more efficient, effective, and inclusive teaching pedagogies, curriculums, and tools. With all of this research, Ni and colleagues noted that for this effort to "have real impact on teaching practices, we eventually need computing instructors to adopt those innovations and integrate them into their own classrooms" [1, p. 544]. Recent efforts, such as the Evidence-Based Teaching Practices in CS SIGCSE Workshop [2], have tried to bridge this gap between published innovations and their adoption in the classroom. Morrison *et al.* [2] conducted a workshop that walked faculty from introducing the intervention to modeling the intervention and ended with providing a list of resources to aid in attendee's implementation efforts once they were back at their institutions. However, an apparent disconnect remains between published research and what is happening in computer science classrooms. Barker reported that "despite widespread development, research, and dissemination of teaching and curricular practices that improve student retention and learning, faculty often do not adopt them" [3, p. 604]. Hovey and colleagues [4] found that CS faculty admitted to lecturing more often than using student-centered instructional techniques when asked. "These results...suggest that there is a need to increase the use of evidence-based teaching practices among CS faculty in higher education" [4, p.483].

While it is tempting to conflate all CS classrooms, the landscape of K12 professional development is strikingly different from the resources offered to Higher Education faculty. With the growing number of K12 Computer Science standards, states releasing teacher certifications, and state legislation including computing requirements in the K12 curriculum, K12 teachers have many training resources to help them pivot into computer science teaching. These include methods courses in Education colleges devoted to training teachers how to teach computer science [5], micro-credentialing offerings which are free, online mini-instructional units covering instructional strategies such as live coding, pair programming, and peer instruction [6], and professional development associated with all of the AP endorsed Computer Science curriculum [7]. In addition, in most states, to maintain a K12 teaching credential, a teacher must show evidence of a certain number of Professional Development hours or Continuing Education credits upon renewal. This means even K12 teachers who have been teaching Computer Science for years will likely be taking advantage of the computer science-specific professional development, keeping them up-to-date with recent pedagogical developments.

With both the previous research on CS faculty in higher education reporting limited adoption of evidence-based teaching interventions and the lack of systematic pressure for continual professional development like in K12, we are left to wonder how faculty learn about and choose to adopt research-based teaching practices.

Literature Review

Existing research on best practices for disseminating research into pedagogical practices in a manner that encourages adoption by CS faculty is limited. Past work primarily focused on dissemination practices within general education without addressing STEM faculty's unique needs [8]. CS educators, in particular, must address distinct and unique needs, such as a higher-than-average attrition rate and a significant gender imbalance—both of which could be alleviated or even mostly eliminated with teaching and curricular adjustments [3], [4]. Educators hear about innovations through funded initiatives such as the NSF or a campus center for teaching and learning (CTL) [4]. However, it's been noted that CTLs are effective at "fostering teaching excellence in the main, they have provided little attention to addressing potentially unique needs of STEM faculty" [8].

Hovey *et al.* [4] found faculty citing informal conversations with peers at their institution or at conference presentations at CAHSI, SIGCSE, FIE, or the NCWIT Summit as their most common source of information on teaching innovations. The most persuasive peer recommendations came from peers with personal connections, such as former mentors, students, or strangers with strong personal or institutional reputations for teaching and/or research [4]. While colleagues are an important source of information on teaching innovations, to the extent that CS departments are physically arranged to facilitate unstructured "water cooler talk" about teaching in casual conversations, research faculty tend to be more likely to mention ideas they heard from research conferences than from local colleagues [3]. However, the CS education community lacks a single comprehensive conference for the entire field, making it difficult for some educators to attend education-oriented workshops and fragmenting the CS community by topical area [9].

While professional development workshops have been shown to have a statistically significant impact on faculty adoption of innovative teaching methods across academic disciplines, CS educators experience a range of challenges in actually adopting a new practice. Thus, professional developers and facilitators need to consider the specific difficulties CS educators face when presenting faculty recommendations [1]. Teaching faculty can be at a disadvantage to research faculty [3]. "CS education conferences are geographically separate from other topical CS conferences—effectively siloing education from other CS research" [9, p 230], meaning that faculty must choose not only the type of conferences they would like to attend but also where to present their work, and what type of work they can perform. This means faculty with limited resources, such as lecturers at smaller schools, may be more likely to skip education-centric conferences to attend research-centric conferences, or they may not be able to participate at all due to time or funding constraints [9].

When innovative teaching methods are disseminated, existing research has noted that it's essential to communicate their value in terms that align with the challenges faced by CS educators. For instance, faculty have described hearing about a new strategy or tool but didn't necessarily have a problem that tool or strategy would address [4]. Faculty were more motivated to adopt a practice or tool because it was framed as a way to reduce the underrepresentation of women and minorities from pursuing CS degrees [4]. However, the existence of research underscoring the value of an approach was found not to be a significant factor in predicting the adoption of a practice, nor was an educator's belief that a new approach would yield positive student learning outcomes. Instead, their decision to adopt was found to be most significantly driven by educator excitement [10]. Educator excitement or interest in a teaching innovation has been identified as a positive factor in facilitating adoption—stimulating a sense of excitement in educators about a particular teaching innovation could be a powerful way to encourage the adoption of a practice [10].

In terms of the adoption of student-centered teaching practices in Computer Science classrooms, research indicates that "CS faculty have adopted student-centered practices to some degree." Still, there remains significant work to be done [11, p. 1].

Looking to Broader STEM Education

Considering STEM subjects more broadly, existing research finds that instructors require more support and guidance in implementing active learning to ensure all students benefit, which could be achieved through educational development interventions [12]. Research into the adoption of student-centered pedagogical practices in engineering schools found that despite significant effort expended by engineering education researchers into providing empirical evidence of the benefits of student-centered teaching strategies, "student-centered strategies have not been widely adopted as many engineering faculty still rely heavily on traditional lectures" [13, p. 923]. Moreover, "no valid framework exists for designing instructional development programs that would equip engineering educators to make [the necessary] changes" to their course design. Consequently, existing programs vary considerably in terms of scope and effectiveness [14, p. 121].

Some work suggests that early-career professional development (PD) programs result in sustained adoption of learner-centered teaching practices. For example, biology postdoctoral participants from the Faculty Institutes for Reforming Science Teaching (FIRST) IV program were found to have "maintained their learner-centered practices and were more learner-centered than their peers" for up to 9 years after finishing the professional development program [15, p. 1].

To summarize the above, existing research on best practices for dissemination models that encourage the adoption of teaching interventions by CS educators is scant. Existing research into best practices in the broader STEM disciplines echoes many of the challenges seen in CS. The rare supported success is often school-specific, offering little in terms of a transferable model applicable to Computer Science education.

Response Hierarchy Models

If existing frameworks aren't transferable or applicable, what does this dissemination process look like? We can find implications and suggestions in previous work. Ni *et al.* [1] and Barker *et al.* [3] frequently reference the end of the process, using words like "adopt." Working backwards, Hovey *et al.* [4] and Barker *et al.* [3] discuss where faculty hear or learn about interventions (ranging from conferences to peers) -- an obvious precursor to adoption. The middle part of the process is harder to nail down. Ni *et al.* [1] describe how CS educators experience various challenges during the implementation process which PD facilitators should consider. We think it's reasonable that educators spend time thinking about these challenges before reaching the end stage of adopting an intervention and see this idea of considering adoption hinted at in Hovey *et al.* [4], where they discuss faculty noting that they did not have a problem that a presented tool or strategy would address. Ni [10] discusses educator excitement being a precursor to their adoption of an intervention.

This workflow of hearing about something, a convoluted middle step, and a final step with a clear outcome like adoption largely resembles the models often utilized in the marketing and advertising to understand customer actions and behavior. A well-known marketing model which captures what is being hinted at in the literature is the AIDA (Awareness, Interest, Desire, Action) model (Figure 1). The AIDA model is used in marketing and advertising as a response hierarchy model that identifies the stages consumers move through when they make decisions (such as purchasing, opening a bank account, etc.). The AIDA model implies that individuals move through a linear decision-making process [16].

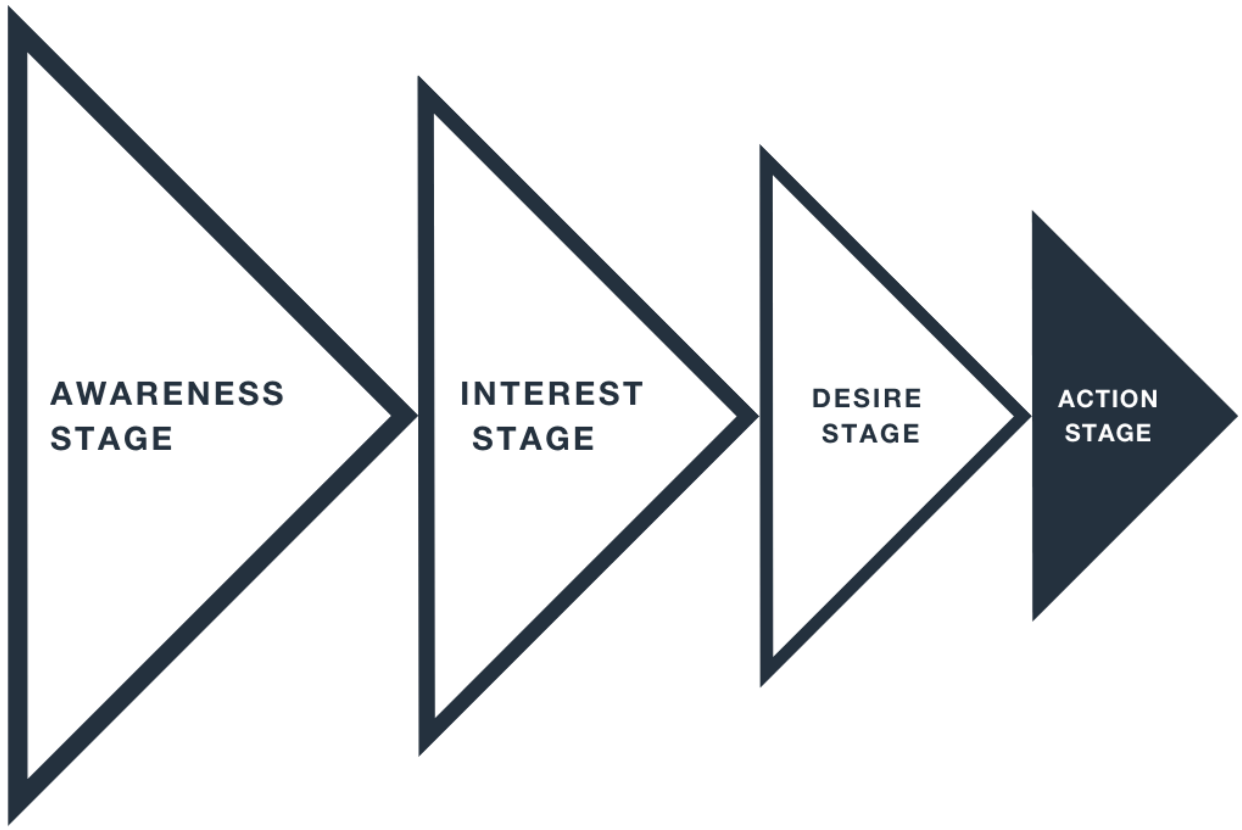

Figure 1: AIDA Model

While the first and last stages probably feel understandable, the interest and desire stages might feel out of place for our context. On the contrary, there is increasing evidence that rather than cognition, emotions underpin decision-making: “Feelings and emotions may be hard to ‘apprehend,’ but they are there nonetheless. Whether people smile, laugh, or chat animatedly about an ad tells you more than a question about whether they think something is interesting or amusing” [17, p. 16]. It would be reasonable to re-cast Hovey’s [4] depiction of faculty stating they don’t have the problem the intervention solves as a loss of interest in the intervention. Similarly, Ni’s [10] discussion of educator excitement resonates with the idea of desire.

Considering the AIDA model in the context of marketing literature, we see that over the last 100 years it has been critiqued and modified many times. For example, the AIDA model has been criticized for assuming that decision-makers experience all stages sequentially and not accounting for emotional or impulsive decisions [18]. Furthermore, the AIDA model incorrectly presumes that human behavior is entirely conscious, rational, and sequential and discounts the influence of emotional reactions in the decision-making process [19]. When weighing these variations, we turned to a more recent study re-interpreting the AIDA model through the lens of neuroscience. Based on “an in-depth analysis of the modern neurological basis of decision-making in humans...the AIDA model is...substantially problematic,” [20, p. 1].

One of the first adjustments the paper offers is mapping the four AIDA stages to three more biological stages: Cognitive (A), Affective (I D), and Behavior (A). This essentially collapses Interest and Desire into a singular stage. Another proffered critique is the observation that the cognitive and affective steps are not as distinct as the linear AIDA model would imply. "From neuroscience vantage point, "interest" cannot be classified as a distinct stage in the human brain, and should be re-classified as "emotionally driven attention" [20, p. 13]. Instead of simply collapsing the model into basically two stages, it is suggested that the "model shall consider massively parallel systems, where A, I, D, and A, have two parallel systems, a conscious and an unconscious. The conscious system must only occur for certain level of unconscious process, whereas unconscious processes can occur without the necessity of consciousness." [20, p. 2]. Our re-interpretation from this critique is that the Cognitive and Affective stages, while distinct, happen simultaneously (Figure 2). Both of these are critical and effect behavior.

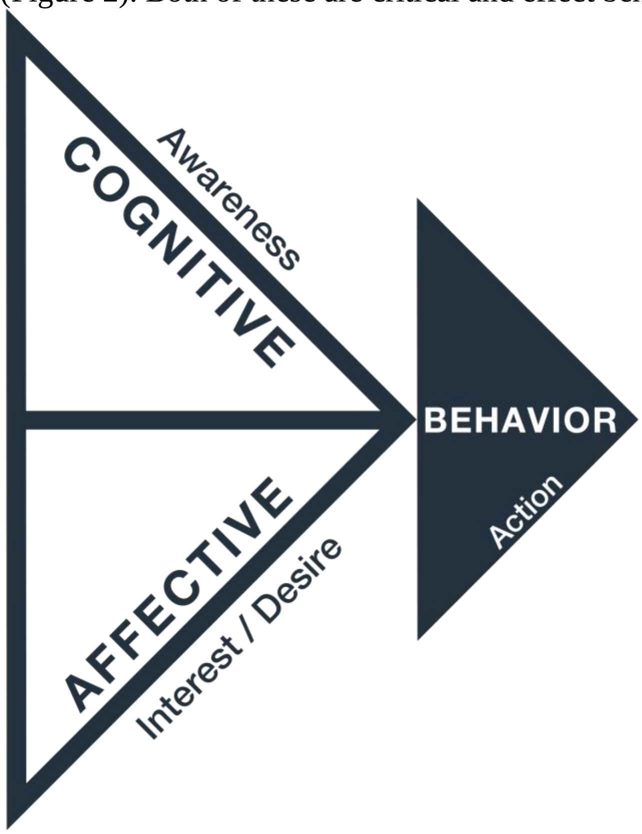

Figure 2: Re-interpretation of AIDA model

Combining the previously reviewed literature with our proposed model, we generate a series of research questions to probe whether this model holds explanatory power in the context of CS Faculty adopting teaching interventions.

RQ1: How does peer-reviewed research affect the adoption of teaching interventions?

Based on previous research, there is conflicting evidence as to whether research affects adoption decisions. To test this considering our model, we break it down into two sub questions.

RQ1a: Are peer-reviewed research publications effective dissemination channels for teaching interventions?
This question probes the Cognitive stage. We look for a relationship between the number of citations about a teaching intervention, which can be thought about as advertising for the intervention, and educator familiarity with the intervention. The results of this question indicate whether an educator's attention was effectively caught by peer-reviewed publications.

RQ1b: Do education research results influence teaching intervention adoption decisions?
This question probes the relationship between Cognitive and Affective. We randomly present educators unfamiliar with an intervention with either a plain or research-filled description (Cognitive) and then see how it affects their perception of the intervention's benefits and challenges (Affective).

RQ2: Which real/perceived benefits and challenges of teaching interventions are most convincing/influential in intervention adoption decisions?

Previous research surrounding what benefits educators find motivating and which challenges they find insurmountable is fragmented. To explore this in the context of our model, we break it down into two sub-questions.

RQ2a: Which real/perceived benefits and challenges of teaching interventions influence an intervention's overall perceived level of benefit and challenge?
This question probes again at the relationship between Cognitive and Affective. We look at how educators' responses to a list of concrete benefits and challenges (Cognitive) influence their overall perception of an intervention as beneficial or challenging (Affective).

RQ2b: Does educator excitement predict intervention adoption decisions?
This question probes the relationship between Affective and Behavior. We look if an educator's overall perception of an intervention as beneficial or challenging (Affective) predicts the rate of educator adoption of an intervention (Behavior).

RQ3: Do certain characteristics of teachers make them more or less likely to adopt evidence-based teaching interventions?

This question looks for confounding variables not accounted for by our proposed model. Notably, "it has been demonstrated that how different preferences and personal characteristics result in different kinds of actions, choices and subsequently decision-making in consumers" [20, p. 9]. We look to see if educator characteristics explain adoption decisions -- a factor that our proposed model would not represent.

Methods

This study consisted of four distinct phases: survey design, survey data collection, systematic literature review for citation counts, and statistical analyses, the results are reported in the next section.

Survey Design

Unlike previous research, we focus specifically on evidence-based pedagogical approaches and technologies specific to computer science education. With this focus in mind, we re-examine motivations and challenges facing professors to see if previous findings on general pedagogical innovations hold when zeroing in on computer science-specific education innovations. Additionally, unlike previous work, we map all of the dimensions of interest (familiarity, implementation, benefits, and challenges) to individual pedagogical approaches/technologies to understand the uniqueness of these different innovations. Finally, we use randomized sampling to present participants who are less familiar with these innovations either plain descriptions or descriptions including evidence-based results. While past research showed that practitioners self-report education research findings about these teaching approaches and tools as unmotivating, we wanted to probe this finding with a behavioral method.

Selecting evidence-based pedagogies

The pedagogical innovations asked about were decided by attempting to balance pedagogical practices and tool adoption as computer science educators may have different beliefs about the best way to improve their teaching. To encourage complete submissions, we limited the number of innovations asked to five of each, creating a total of ten innovations.

The five pedagogical practices were systematically selected from the Pedagogic Approaches Chapter of The Cambridge Handbook of Computing Education Research [21] to cover the pedagogical approaches (see two leftmost columns in Table 1). The MOOC pedagogical approach was removed as it is drastically different from the others and meaningfully unique from classroom-based approaches. For each of the non-MOOC practices, we searched in the ACM digital library to get a citation count. Our searches were limited to the three education-focused conference proceedings (ICER, SIGCSE, and ITiCSE) to ensure citations were part of the computer science education community. The range of publication dates was limited to 2010-2020 to prevent outdated or disproven practices from appearing on the survey. With the relevant citation count for each practice from these steps, the practice with the highest citation count for each pedagogical approach was chosen (see the rightmost two columns in Table 1). This process is an attempt to increase the likelihood of familiarity by the participants.

Table 1: Selecting a Practice for each Pedagogic Approach based on citations

Pedagogic Approach	**Practice**	**ACM results**	**Selected Practices**
Active Learning	Parson’s Problems	45	Test-Driven development
	Test-Driven development	91	
	Test-First development	7	
	Live Coding	44	
Collaborative Learning	Peer Instruction	180	Peer instruction

	Studio-based Learning	32	
	Peer Review	93	
	Think-Pair-Share	24	
	Tech-assisted collaborative note taking	2	
Cooperative Learning	Jigsaw	18	Pair Programing
	Pair Programming	284	
	POGIL	60	
Contributing Student Pedagogy	Content Creation	18	Peer assessment or review
	Activity Creation	2	
	Peer assessment or review	121	
Blended Learning	Flipped classroom	89	Flipped Classroom

The five tool types are directly from Section 21.5 of The Cambridge Handbook of Computing Education Research [22]. The tool types are (1) tools that support writing code, (2) games that teach programming, (3) assessment and feedback tools, (4) code visualizers/simulators, and (5) E-Books.

Re-examining motivations and challenges

The survey has been created by the research team but attempted to directly build and possibly recreate the findings of Hovey *et al.* [4]. The options, specifically for benefits and challenges questions, come directly from previous research findings [4] and are listed in Table 2, below.

Table 2: Options for specifying Benefits and Challenges from Hovey et al. [4]

Benefits	**Challenges**
1. Improved student understanding of content 2. Increased student engagement/interest 3. Improved student grade performance 4. Increased student participation in class 5. Better preparation for students' future careers 6. More inclusive of underrepresented students 7. Improved student social skills	1. Not enough time 2. Satisfied with how I teach currently 3. Lack of access to resources needed to try this 4. Unfamiliar with resources/logistics needed 5. Mis-match with students I teach 6. Not enough evidence it works 7. Students might not like it 8. Slow down material coverage

8. Increased coverage of material 9. Increased teacher time savings	9. Incompatible classroom setup 10. Too large of a class size 11. Too small of a class size 12. Interfere with tenure/promotion 13. Discouraged by colleague or peer 14. Department sets curriculum

This is so we could directly compare our results about benefits/motivations and challenges with their findings. To limit further complexity, other response options were limited to either Yes/No or a 4-point Likert scale (e.g., Strongly Disagree, Disagree, Agree, Strongly Agree) to avoid neutral answers.

Mapping dimensions to individual interventions and randomized descriptions

For each of these 10 interventions, respondents were asked:

1. Familiarity with the intervention [4-point Likert]
2. Have they previously implemented the intervention [Yes/No]

If the respondent has indicated they are unfamiliar with the intervention by selecting one of the lower 2 options of Likert, they are presented with either a plain or research description at random.

3. It would be beneficial to implement this intervention [4-point Likert]
4. What types of benefits would you expect from implementing this intervention? [Options from Hovey *et al.* [4]– see Table 2]
5. It would be challenging to implement this intervention [4-point Likert]
6. What types of challenges would you expect from implementing this intervention? [Options from Hovey *et al.* [4] – see Table 2]

To not skew perceived benefits and challenges, we ask about intent to implement after all the benefits and challenges as participants might try to "rationalize" or "explain" their intent. In this same section, we asked about the familiarity and implementation of an additional eleven evidence-based, computer science-specific pedagogical approaches, those not chosen as the five pedagogical practices selected from Chapter 15 of The Cambridge Handbook of Computing Education Research [21] – as reproduced in the second column of Table 1- at the end. Due to this survey design, the first analysis below includes a larger set of practices and tools.

Additionally, we left our demographic collection until the end of the survey as calling attention to demographics has the potential skew answers. Demographic questions included the faculty member's highest level of education, the field of their highest degree, number of years teaching computer science, total number of years teaching, number of years in industry (non-teaching roles), and the institution types they currently teach at.

Survey Data Collection

We emailed 5,548 computer science lecturers and professors who have taught in the United States a URL to our survey hosted on SurveyMonkey. The survey took participants an average of 16 minutes and 7 seconds to complete, as measured by the SurveyMonkey software.

Respondents were not required to complete any of the questions. Out of the 273 CS and STEM instructors (professors and lecturers) who participated in the survey, 105 completed it. Of these 105, 3 did not indicate they were higher education instructors (indicating with K12 or nothing). In the following analyses, only higher education respondents who completed the survey were included. Assuming the population of postsecondary computer science teachers is 32,430 based on US Bureau of Labor and Statistics, if we want a confidence interval of 95% (industry standard) and are aiming for a margin of error of <10%, then we need a minimum sample size of 96 completed surveys. This supports that the 102 respondents included in the analyses below are a reasonable sample size given the population.

Respondent Demographics

To get a sense of who answered the survey, we present a summary of our demographic questions. To qualify for the survey, respondents indicated they were a past or present CS or computing-related educator who has taught in the United States. 48 respondents taught at a 4-year research institution, 40 at a 4-year teaching university and 13 taught at a community or technical college. 74 respondents had a doctorate degree, while 24 respondents reported a Master's degree, and 1 reported a 4-year degree. The majority of respondents had spent most of their career teacher. Additionally, the vast majority of respondents (over 90%) had only or mostly taught computing or Computer Science.

Limitations to collection methods

This way of recruiting participants has clear limitations. Most notably, we recruited participants from a database built in a proprietary, non-randomized, or representative way. It follows that the resulting sample is also possibly skewed in unpredictable ways.

It should also be noted that this data was collected from May 2020 through October 2020, during the beginning of the COVID-19 pandemic when many educators were actively changing from in-person to online instructional methods.

Systematic Literature Review for Citation Counts

For the first research question, we required at least the beginning of a systematic literature review. Instead of doing a full review, we generated raw citation counts to get a rough sense of how much an intervention was being talked about by the research community. Similar to how we selected our pedagogical practices when designing our survey, we conducted our search on the ACM digital library. Citations for each pedagogical method were searched for in the SIGCSE, ICER, and ITiSCE proceedings dated between 2010 to 2020 to prevent outdated or disproven practices from appearing on the survey.

Operationalization of Educator Excitement

As we did not directly ask about educator excitement about the selected interventions, we posit that educators would be excited when they can realize measurable benefits without a significant amount of work. In our preliminary analysis of this data, we operationalized educators' overall excitement as the number of interventions they found beneficial minus the number of interventions they found challenging. We found that an educator's excitement predicted both the number of evidence-based interventions they had implemented and wanted to implement. "When investigating if combining perceived challenges and benefits were necessary, we found that individually these components had half the explanatory power" [23, p. 1342].

In this study, we slightly modify this promising operationalization. For RQ1b and RQ2b, we operationalize excitement by taking the overall perception of an intervention's benefit and subtracting overall perception of how challenging an intervention is to implement. This allows us to measure the excitement about an *individual* intervention, unlike our previous operationalization which gave us an educator's excitement *across* interventions. For RQ3, we used our prior operationalization of excitement.

Statistical Analyses

For each of the different research questions, a different statistical analysis was done. This section and the results section are presented in the order of our research questions for easy reference between the methods and results.

RQ1a: Are peer-reviewed research publications effective dissemination for teaching interventions?

To address this question, we ran a linear regression analysis using Excel to test whether the number of research publications for a given intervention could predict the average level of educator familiarity with that intervention. A linear regression is an appropriate match to the data due to the continuous nature of the citation data, ranging from 2 to 314 papers, and the continuous nature of average educator familiarity, ranging from 1.45 to 2.79. Linear regression is also appropriate in terms of testing whether a predictive relationship exists between these two variables. Suppose a positive correlation with a non-trivial effect size (reported as the r statistic) is found. In that case, we will be able to reasonably conclude that peer-reviewed research publications are an effective dissemination for teaching interventions.

RQ1b: Do education research results influence teaching intervention adoption decisions?

To address this question, we ran a series of one-way ANOVAs using Excel. Our 1 x 2 factorial design separated the respondents into either the plain description group or the research description group. For each intervention, we tested three different dependent variables: perceived level of benefit of the intervention, perceived level of challenge of the intervention, and educator excitement level about the intervention which we operationalized as the perceived benefit level minus the perceived challenge level. This design of testing each of the 10 interventions for 3 different dependent variables resulted in 30 potential ANOVAs. As we are measuring 30 *different* dependent variables, there is no need for a correction.

While these dependent variables are ordinal as they were Likert scales on the survey, we mapped the 4 point Likert scale (Strongly Disagree, Disagree, Agree, Strongly Agree) onto numbers (-2,-1,1,2) resulting in a quantitative dependent variable. The data thus fit the ANOVA statistical test which requires a categorical independent variable (whether the respondent was the plain or research-based description of the intervention) and a quantitative dependent variable (the respondents perceived level of benefit, challenge and excitement about implementing the interventions).

An ANOVA analysis also addresses the research question as statistical significance would suggest that educators who read research-filled descriptions of interventions have different perceptions about teaching interventions than those who read plain descriptions. Similarly, the calculated Eta squared value (η^2), which is the effect size statistic, addresses the implicit follow up question of *how much* does research affect educators' perceptions of a teaching intervention.

RQ2a: Which real/perceived benefits and challenges of teaching interventions influence the overall perceived level of benefit and challenge of an intervention?

To address this question we did a series of Welch's t-tests, or unequal variances t-tests, with R's t.test function which determines if two groups have a significant difference between their mean. Each t-test investigated a specific benefit or challenge being asked about an intervention. The respondents were separated into two groups, depending on whether they indicated they thought the benefit or challenge in question applied to that intervention. Then, with the independent variable being whether or not the respondent saw the benefit or challenge, we tested the overall perceived level of benefit or level of challenge to implement the given intervention.

For example, one t-test separated respondents on whether they thought Test-Driven Development improved student understanding. Group 1 responded No, and Group 2 responded Yes. We then used the t-test to compare the average level of benefit the respondents saw in Test Driven Development. If a particular benefit influenced the community's perception of the intervention being beneficial, we'd expect the mean of one group to be statistically significantly different from the other group.

Due to the repetitive testing on the dependent variables, significance will be tested against a Bonferroni corrected alpha value. Given the nine unique benefits being tested against each perception of how beneficial an intervention is, a *p-value* of less than .006 is required for statistical significance. Given the 14 unique challenges being tested against each perception of how challenging an intervention is to implement, a *p-value* of less than .004 is required for statistical significance. As the group sizes are dependent upon respondents' answers to each benefit, the two groups were frequently different sizes. Due to this characteristic of the data, we report Hedges' g instead of Cohen's d for effect size.

RQ2b: Does educator excitement predict intervention adoption decisions?

To address this question, we ran a linear regression analysis in Excel to test whether the level of educator excitement (operationalized as the level of benefit minus level of challenge to implement) for a given intervention could predict the percentage of educators who adopted that intervention. A linear regression is an appropriate match to the data due to the continuous nature of the independent variable, the level of excitement, ranging from -0.157 to 1.480, and the continuous nature of percent of adoption, ranging from .253 to .727.

Linear regression is also appropriate in terms of testing whether a predictive relationship exists between these two variables. If a positive correlation with a non-trivial effect size (reported as the *r* statistic) is found, we can reasonably conclude that the level of educator excitement about the intervention predicts implementation of the intervention.

RQ3: Do certain aspects of teachers make them more or less likely to adopt evidence-based teaching interventions?

To address this question, we did a series of Welch's t-tests, or unequal variances t-tests with R's t.test function. The educator characteristics we tested were: (1) whether an educator had experience teaching a non-CS course or not, (2) whether an educator had spent more years in industry or more years teaching, and (3) whether an educator worked at a research or teaching institution. We also tested different dependent variables: (1) overall excitement about teaching interventions (operationalized as the number of interventions they perceived as beneficial minus the number of interventions they perceived as challenging to implement), (2) number of implemented teaching interventions, and (3) number of teaching interventions they intended to implement in the future. This resulted in 9 different t-tests.

For example, one t-test separated respondents on whether they had teaching experience outside of CS. Group 1 only had teaching experience in CS and Group 2 had taught non-CS courses. We then used the t-test to compare the average number of evidence-based interventions implemented by each group. If a particular characteristic was influential on whether educators were more or less likely to implement evidence-based interventions, we'd expect the mean of one group to be statistically significantly different from the other group.

Due to the repetitive testing on the dependent variables, significance will be tested against a Bonferroni corrected alpha value. Given the 3 educator characteristics being tested against each dependent variable, a *p-value* of less than .017 is required for statistical significance. As the group sizes are dependent upon respondents' answers to each benefit, the two groups were frequently different sizes. Due to this characteristic of the data, we report Hedges' g instead of Cohen's d for effect size.

Results

This section and the above methods section are presented in the order of our research questions for easy reference between the methods and results.

RQ1a: Are peer-reviewed research publications effective dissemination for teaching interventions?

From the linear regression analysis, we calculated the test statistic, *t,* as 3.254 with a corresponding *p-value* of 0.00576, which indicates statistical significance based on our 95% confidence threshold and corresponding 0.05 alpha value. The calculated effect size, Pearson's correlation coefficient, *r,* was 0.656, which indicates a strong correlation according to Haden's threshold of 0.6 (Haden, 2019). A graphical representation of the linear regression is presented below in Figure 3.

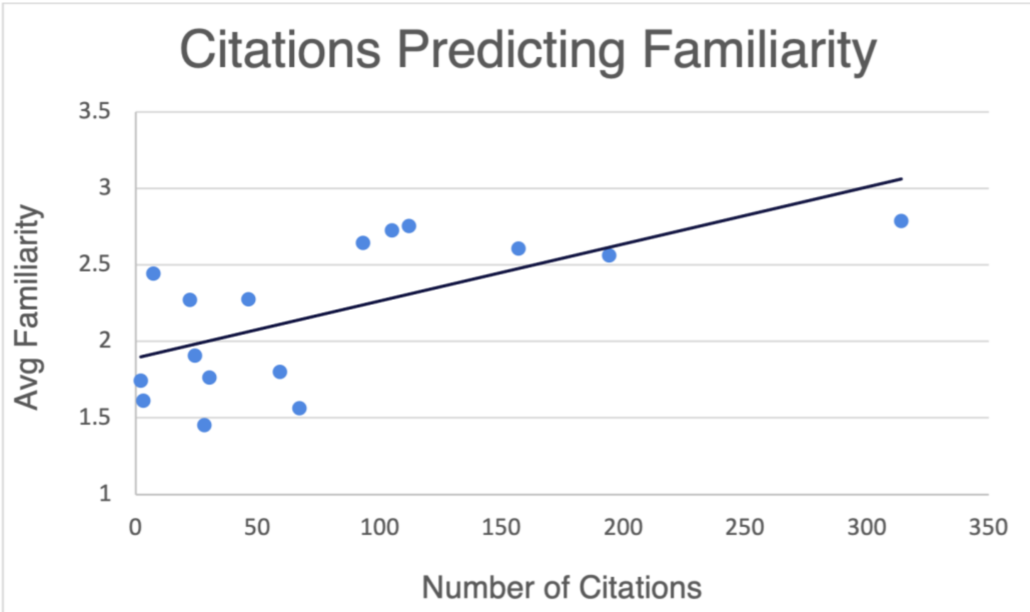

Figure 3: Linear Regression showing correlation between the number of citations and faculty familiarity

As we found statistical significance and a strong correlation, we conclude that the number of peer-reviewed publications about a teaching intervention can predict educator familiarity with that teaching intervention. As this is a correlation, we cannot claim that these peer-reviewed publications *directly cause* educator awareness, but it seems reasonable to claim that peer-reviewed publications are an effective part of a dissemination plan.

A potential confounding factor could be the fact that we limited our citation search to peer-reviewed publications in conference proceedings. Further work would need to disambiguate if journal-based publication, without a corresponding conference event, still leads to educator familiarity. Similarly, non-peer-reviewed literature such as books and websites could also play a factor in dissemination, not captured by the statistical analysis we present.

RQ1b: Do education research results influence teaching intervention adoption decisions?

We summarize the findings of our series of one-way ANOVAs in Table 3. The evidence-based intervention being described in plain language or with research citations represent the rows. For each of these interventions, these two groups were investigated to see if seeing a research-based description influenced the number of identified benefits, number of identified challenges or excitement, operationalized by subtracting the number of challenges from the number of benefits. These three dependent variables are represented by the columns.

Each interior cell of the table represents an ANOVA we run and contains the test statistic, F, the *p-value*, and the effect size or Eta squared value (η^2). We have indicated the two ANOVAs which found significance at the 95% threshold with slight shading of the cell. Three of our

ANOVAs, the ones for EBooks, did not have sufficient enough data to run the test as EBooks are so well-known in the community that there were not enough people who were presented with the descriptions.

Table 3: ANOVA results of whether research-infused descriptions of pedagogical interventions affect faculty perceptions

Evidence-based Intervention	**Number of Identified Benefits**	**Number of Identified Challenges**	**Excitement or Benefits-Challenges**
Test-driven Development	F = 0.27731 p = 0.60199 η^2 = 0.00833	F = 2.89240 p = 0.09870 η^2 = 0.08289	F = 1.76506 p = 0.19339 η^2 = 0.05227
Peer Instruction	F = 0.75265 p = 0.39108 η^2 = 0.01981	F = 1.08415 p = 0.30471 η^2 = 0.02923	F = 1.58956 p = 0.21550 η^2 = 0.04229
Pair Programming	F = 4.25099 p = 0.05586 η^2 = 0.20992	F = 0.70351 p = 0.41570 η^2 = 0.04785	F = 0.41037 p = 0.53213 η^2 = 0.02848
Peer Assessment	F = 4.72886 p = 0.03768 η^2 = 0.13616	F = 0.44891 p = 0.50815 η^2 = 0.01524	F = 3.52285 p = 0.07062 η^2 = 0.10832
Flipped Classroom	F = 3.27506 p = 0.08619 η^2 = 0.14703	F = 0.08091 p = 0.77996 η^2 = 0.00537	F = 0.06096 p = 0.80833 η^2 = 0.00405
Tools that Support Writing Code	F = 0.00892 p = 0.92529 η^2 = 0.00025	F = 0 p = 1 η^2 = 0-	F = 0.02393 p = 0.87800 η^2 = 0.00072
Games that teach programming	F = 4.04623 p = 0.04937 η^2 = 0.07093	F = 1.37243 p = 0.24706 η^2 = 0.02725	F = 0.21628 p = 0.64395 η^2 = 0.00439
Assessment and Feedback Tools	F = 0.17241 p = 0.68093 η^2 = 0.00571	F = 1.97946 p = 0.17086 η^2 = 0.06831	F = 2.50663 p = 0.12501 η^2 = 0.08495
Code Visualizers/ Simulators	F = 0.08110 p = 0.77736 η^2 = 0.00213	F = 0.14593 p = 0.70470 η^2 = 0.00404	F = 0.00053 p = 0.98178 η^2 = 1.46972E-05
E-Books	sample size too small		

Due to the underwhelming amount of statistical significance, and low effect size (accounting for only 13.6% and 7.1% of the variance), we conclude that the educators do not seem influenced by research findings when considering the benefits and challenges of implementing a teaching intervention.

RQ2a: Which real/perceived benefits and challenges of teaching interventions influence the overall perceived level of benefit and challenge of an intervention?

We summarize the findings of the series of Welch's t-tests, or unequal variances t-tests which explore which specific benefits and challenges affect educator's perception of an intervention's overall level of benefit or level of challenge to implement in the tables below. The teaching interventions are represented as rows, and the specific benefits and challenges are represented as columns. Table 4 is all of the benefits. Table 5 and Table 6 are the same interventions, with half of the specific challenges on each.

Each interior cell of the table represents a t-test we ran and contains the test statistic, *t*, the *p-value*, and the effect size or Hedge's g. As explained above, due to repeated testing on dependent variables, the corrected alpha value is .006 for the benefits table and .004 for the two challenges tables.

Looking at the individual benefits across the interventions, improved student understanding, increased student engagement, and increased preparation for future career were statistically significant benefits on the impression of an intervention's benefit level. These were closely followed by improved grades which was significant for 9 out of the 10 interventions, and increased student participation which was significant for 8 out of the 10 interventions. In addition, increased teacher time savings (7 out of 10), greater material coverage (6 out of 10), improved student social skills (6 out of 10), and being inclusive (5 out of 10) were significant for some interventions but not others. Overall, the benefits table indicates that while student-centric benefits are more generally influential on a teacher's perception of a teaching intervention, we cannot assume that on a list of benefits of a teaching intervention all the benefits have the same or any impact on the educator's perception of the intervention.

Looking at the individual challenges across the interventions, the potential to interfere with tenure or promotion, and a department that sets the curriculum, which were both significant for 4 out of the 10 interventions, were the most influential challenges overall. These were followed by being unfamiliar with the resources and logistics needed to implement an intervention, incompatible classroom setup, having a class size that was too large, and being discouraged by a peer, which were all significant for 2 out of the 10 interventions. Only these 6 out of the 14 individual challenges were found statistically significant for at least 2 interventions. These findings suggest educators were most dissuaded by challenges that are caused by an institution's infrastructure and culture. Similar to the benefits analysis, we see that while there are trends to which challenges are frequently faced, we cannot assume that all challenges are seen the same or even relevant for each intervention.

Table 4: Summary of Welch's T-tests for Intervention and Perceived Benefits

Intervention	Improved Understanding	Increased Engagement	Improved Grades	Increased Participation	Career Preparation	Inclusive	Social Skills	Greater Material Coverage	Time Savings
Test-Driven Development	t = 4.1809 p = 0.00017 g = -1.1311	t = 4.3306 p = 3.672e-05 g = -0.7939	t = 3.4027 p = 0.00095 g = -0.5806	t = 3.899 p = 0.00020 g = -0.6691	t = 3.677 p = 0.00090 g = -1.1099	t = 3.4188 p = 0.00210 g = -0.7522	t = 3.5591 p = 0.00198 g = -0.7422	t = 3.4236 p = 0.00125 g = -0.6142	t = 3.899 p = 0.00020 g = -0.6691
Peer Instruction	t = 4.4623 p = 0.00018 g = -1.5724	t = 4.3743 p = 0.00012 g = -1.2780	t = 3.0231 p = 0.00323 g = -0.5444	t = 5.0522 p = 2.532e-05 g = -1.5627	t = 3.7068 p = 0.000378 g = -0.6995	t = 3.6014 p = 0.00050 g = -0.6376	t = 3.9868 p = 0.00023 g = -0.9565	t = 2.0358 p = 0.04766 g = -0.3684	t = 2.0648 p = 0.04179 g = -0.3479
Pair Programming	t = 7.3452 p = 5.631e-09 g = -1.9016	t = 7.2436 p = 5.258e-09 g = -1.7958	t = 5.4179 p = 4.773e-07 g = -0.9092	t = 6.4905 p = 1.186e-08 g = -1.2662	t = 6.2534 p = 2.416e-08 g = -1.1723	t = 6.0294 p = 3.005e-08 g = -1.0123	t = 6.742 p = 1.033e-08 g = -1.4661	t = 4.2098 p = 0.00018 g = -0.7272	t = 4.407 p = 2.6e-05 g = -0.6792
Peer Assessment	t = 3.0547 p = 0.00287 g = -0.5082	t = 4.0815 p = 0.00010 g = -0.6366	t = 3.1651 p = 0.00249 g = -0.4857	t = 3.468 p = 0.00079 g = -0.5128	t = 3.4591 p = 0.00080 g = -0.5095	t = 1.7806 p = 0.15 g = -0.4899	t = 3.1743 p = 0.00203 g = -0.4574	t = 1.6104 p = 0.23 g = -0.5732	t = 2.1631 p = 0.04949 g = -0.3873
Flipped Classroom	t = 5.9983 p = 1.514e-07 g = -1.3106	t = 6.1247 p = 3.607e-08 g = -1.1658	t = 5.3132 p = 6.472e-07 g = -0.9218	t = 6.0892 p = 8.493e-08 g = -1.3106	t = 4.2773 p = 4.567e-05 g = -0.7664	t = 2.7834 p = 0.00714 g = -0.4588	t = 3.3659 p = 0.00112 g = -0.5404	t = 4.7023 p = 8.737e-06 g = -0.8067	t = 3.3997 p = 0.00137 g = -0.6011
Tools that Support Writing Code	t = 5.1207 p = 5.429e-06 g = -1.2183	t = 3.0921 p = 0.00260 g = -0.5471	t = 2.3306 p = 0.02189 g = -0.4315	t = 2.7936 p = 0.00699 g = -0.4758	t = 3.341 p = 0.00132 g = -0.6513	t = 1.4733 p = 0.1461 g = -0.2372	t = 1.7322 p = 0.1114 g = -0.3996	t = 3.2469 p = 0.00190 g = -0.6468	t = 3.4927 p = 0.00087 g = -0.6900
Games that teach programming	t = 7.5716 p = 1.892e-11 g = -1.3899	t = 7.081 p = 1.603e-09 g = -1.4831	t = 5.5889 p = 2.378e-07 g = -1.0015	t = 6.5914 p = 2.573e-09 g = -1.2809	t = 3.82 p = 0.00075 g = -0.8373	t = 4.4508 p = 4.04e-05 g = -0.7912	t = 3.82 p = 0.00075 g = -0.8373	t = 3.2589 p = 0.00383 g = -0.7634	t = 6.0709 p = 8.122e-07 g = -1.0266
E-Books	t = 4.8419 p = 4.688e-06 g = -0.8704	t = 5.008 p = 2.301e-06 g = -0.8930	t = 4.7882 p = 6.37e-06 g = -0.8381	t = 4.2045 p = 0.00012 g = -0.7812	t = 4.1171 p = 0.00011 g = -0.7372	t = 2.5581 p = 0.01198 g = -0.4287	t = 1.2942 p = 0.2388 g = -0.3601	t = 4.2496 p = 4.714e-05 g = -0.7432	t = 6.1754 p = 2.736e-08 g = -1.0894
Assessment & Feedback Tools	t = 3.8079 p = 0.00031 g = -0.7816	t = 4.0964 p = 8.979e-05 g = -0.7636	t = 3.8876 p = 0.00022 g = -0.7836	t = 2.5203 p = 0.01359 g = -0.4444	t = 4.6839 p = 8.717e-06 g = -0.8311	t = 2.0456 p = 0.04346 g = -0.3514	t = 0.58583 p = 0.5667 g = -0.1428	t = 2.3455 p = 0.02293 g = -0.4146	t = 2.3301 p = 0.02198 g = -0.4478

Code Visualizers/ Simulators	t = 5.4772 p = 2.372e-05 g = -2.1168	t = 5.1747 p = 2.293e-06 g = -1.0488	t = 4.4198 p = 3.104e-05 g = -0.8421	t = 4.9964 p = 2.601e-06 g = -0.8550	t = 3.542 p = 0.00064 g = -0.6519	t = 3.7544 p = 0.00037 g = -0.6415	t = 1.8889 p = 0.1172 g = -0.5763	t = 2.3042 p = 0.02608 g = -0.4894	t = 3.4778 p = 0.00107 g = -0.6584

Table 5: Summary of Welch's T-tests for Intervention and Perceived Challenges

Intervention	**No Time**	**Satisfied with How I Currently Teach**	**Lack of Resources**	**Unfamiliar with Resources/Logistics Needed**	**Mismatch with Students I Teach**	**Not Enough Evidence it Works**	**Students Might Not Like It**
Test-Driven Development	t = 4.7722 p = 1.126e-05 g = -1.0250	t = 0.29474 p = 0.7705 g = -0.0722	t = 2.5795 p = 0.01213 g = -0.4962	t = 1.6901 p = 0.0949 g = -0.3234	t = 0.03914 p = 0.9692 g = -0.0122	t = 1.1301 p = 0.272 g = -0.2753	t = 1.7237 p = 0.08878 g = -0.3388
Peer Instruction	t = 0.02147 p = 0.9829 g = -0.0043	t = -2.9426 p = 0.00412 g = 0.3205	t = -0.47612 p = 0.6374 g = 0.1067	t = 0.80189 p = 0.4284 g = -0.2140	t = 0.09190 p = 0.9281 g = -0.0299	t = 0.25409 p = 0.8044 g = -0.0976	t = -0.20703 p = 0.8364 g = 0.0403
Pair Programming	t = -0.2183 p = 0.828 g = 0.0463	t = 0.59827 p = 0.5613 g = -0.2337	t = -0.73911 p = 0.4675 g = 0.1720	t = -3.7264 p = 0.00036 g = 0.4607	t = 2.3945 p = 0.02436 g = -0.7928	t = 0.8819 p = 0.4052 g = -0.4574	t = 0.43707 p = 0.663 g = -0.0844
Peer Assessment	t = 1.4252 p = 0.1574 g = -0.2767	t = 2.477 p = 0.03225 g = -0.7459	t = 6.9638 p = 4.035e-10 g = -0.9033	t = 4.6985 p = 1.087e-05 g = -0.8398	t = 0.895 p = 0.3787 g = -0.2324	t = -0.01653 p = 0.9871 g = 0.0051	t = 2.2446 p = 0.02732 g = -0.4481
Flipped Classroom	t = -0.5228 p = 0.6023 g = 0.1012	t = -0.63831 p = 0.5354 g = 0.1829	t = -0.1283 p = 0.8985 g = 0.0286	t = 0.98628 p = 0.3379 g = -0.3284	t = 1.1199 p = 0.2743 g = -0.3328	t = 0.70554 p = 0.505 g = -0.3555	t = -0.32375 p = 0.7468 g = 0.0627
Tools that Support Writing Code	t = 1.0581 p = 0.2941 g = -0.2282	t = 0.22792 p = 0.8247 g = -0.0870	t = 1.5285 p = 0.1318 g = -0.3370	t = 0.4793 p = 0.6332 g = -0.0996	t = 0.04906 p = 0.9631 g = -0.0250	t = 0.70673 p = 0.5093 g = -0.3809	t = -0.28738 p = 0.7762 g = 0.0720
Games that teach programming	t = 0.52833 p = 0.5985 g = -0.1032	t = 1.4799 p = 0.1563 g = -0.4031	t = 0.13748 p = 0.891 g = -0.0276	t = 2.2114 p = 0.02944 g = -0.4188	t = 4.9363 p = 1.413e-05 g = -0.7729	t = 0.47345 p = 0.6393 g = -0.1168	t = 1.9406 p = 0.06382 g = -0.4968

E-Books	t = -0.24505 p = 0.8079 g = 0.0563	t = 0.94526 p = 0.3741 g = -0.5095	t = -1.009 p = 0.3198 g = 0.2050	t = -0.07682 p = 0.9393 g = 0.0189	t = 1.0382 p = 0.3373 g = -0.6304	t = 1.1392 p = 0.3045 g = -0.7918	t = 1.0228 p = 0.3149 g = -0.2863
Assessment and Feedback Tools	t = -0.21947 p = 0.8267 g = 0.0424	t = 0.83903 p = 0.4624 g = -0.9892	t = -1.0159 p = 0.3121 g = 0.1840	t = -0.62031 p = 0.5368 g = 0.1168	t = 0.70733 p = 0.5049 g = -0.4745	t = 0.79615 p = 0.4697 g = -0.7483	t = 0.21248 p = 0.8338 g = -0.0617
Code Visualizers/ Simulators	t = 1.3738 p = 0.1731 g = -0.2716	t = 0.40401 p = 0.7 g = -0.1334	t = 2.4237 p = 0.01717 g = -0.4704	t = 2.2923 p = 0.02397 g = -0.4443	t = 0.66857 p = 0.5268 g = -0.3283	t = -0.20011 p = 0.846 g = 0.0917	t = -0.29231 p = 0.7785 g = 0.1059

Table 6: Summary of Welch's T-tests for Intervention and Perceived Challenges

Intervention	**Slow down material coverage**	**Incompatible Classroom Setup**	**Class Size Too Large**	**Class Size Too Small**	**Could Interfere w/ Tenure or Promotion**	**Discouraged by a Peer**	**Department Sets Curriculum**
Test-Driven Development	t = 1.5425 p = 0.126 g = -0.2957	t = 0.35877 p = 0.7311 g = -0.1768	t = 4.7665 p = 6.662e-06 g = -0.4976	N/A	t = 4.7354 p = 7.077e-06 g = -0.4655	t = -0.33477 p = 0.7685 g = 0.2297	t = -1.1332 p = 0.28 g = 0.4250
Peer Instruction	t = 0.7306 p = 0.4676 g = -0.1560	t = -0.85763 p = 0.3951 g = 0.1663	t = 2.0389 p = 0.05303 g = -0.7409	t = 0.33425 p = 0.7459 g = -0.1417	t = 0.86301 p = 0.5462 g = -1.6423	t = 1.8575 p = 0.1114 g = -1.4967	t = 0.56893 p = 0.5929 g = -0.3569
Pair Programming	t = 0.17945 p = 0.8586 g = -0.0429	t = 0.58609 p = 0.5611 g = -0.1411	t = 0.04587 p = 0.9638 g = -0.0124	t = -0.02998 p = 0.9767 g = 0.0107	t = -3.6697 p = 0.00039 g = 0.3643	t = -3.6719 p = 0.00039 g = 0.3681	t = -3.6766 p = 0.00039 g = 0.3761
Peer Assessment	t = 0.25111 p = 0.8028 g = -0.0528	t = 4.4552 p = 7.236e-05 g = -0.6428	t = -0.66723 p = 0.5105 g = 0.1724	t = 0.61445 p = 0.555 g = -0.2031	t = 6.9498 p = 3.536e-10 g = -0.6831	t = 7.0158 p = 2.981e-10 g = -0.7176	t = 6.9819 p = 3.254e-10 g = -0.6999
Flipped Classroom	t = 1.7553 p = 0.1018 g = -0.6967	t = 1.5263 p = 0.146 g = -0.5437	t = 2.0276 p = 0.06756 g = -0.9066	N/A	t = 0.68755 p = 0.6156 g = -0.9276	t = 0.84999 p = 0.432 g = -0.4885	t = -4.4944 p = 1.863e-05 g = 0.4461

Tools that Support Writing Code	t = 0.96221 p = 0.352 g = -0.3371	t = 0.54112 p = 0.6063 g = -0.2560	t = 1.0679 p = 0.3182 g = -0.5047	N/A	N/A	t = 1.105 p = 0.3473 g = -0.8158	t = 0.88719 p = 0.4229 g = -0.5548
Games that teach programming	t = 1.2379 p = 0.2206 g = -0.2491	t = -0.01076 p = 0.9917 g = 0.0042	t = -0.01446 p = 0.9887 g = 0.0043	N/A	N/A	t = -0.51094 p = 0.6974 g = 0.4209	t = 0.18727 p = 0.8682 g = -0.1361
E-Books	t = 0.49441 p = 0.6459 g = -0.3218	t = -3.496 p = 0.00071 g = 0.3505	t = 32.639 p = 2.2e-16 g = -3.2082	N/A	t = -3.4922 p = 0.00071 g = 0.3433	t = 0.5997 p = 0.5899 g = -0.4869	t = -3.4941 p = 0.00071 g = 0.3468
Assessment and Feedback Tools	t = 0.41891 p = 0.6817 g = -0.1546	t = -2.2817 p = 0.0246 g = 0.2265	t = 0.75224 p = 0.4849 g = -0.5885	t = -2.2831 p = 0.02458 g = 0.2335	N/A	t = -2.2817 p = 0.0246 g = 0.2265	t = 1.9093 p = 0.1958 g = -3.3939
Code Visualizers/ Simulators	t = 1.1926 p = 0.2497 g = -0.3550	t = -0.35622 p = 0.7289 g = 0.1391	t = -0.59095 p = 0.5845 g = 0.3309	N/A	N/A	t = 0.82967 p = 0.4516 g = -0.2126	t = 0.15458 p = 0.891 g = -0.1295

RQ2b: Does educator excitement predict intervention adoption decisions?

From the linear regression analysis, we calculated the test statistic, *t*, as 2.457 with a corresponding *p-value* of 0.0395 which indicates statistical significance based on our 95% confidence threshold and corresponding 0.05 alpha value. The calculated effect size, Pearson's correlation coefficient, *r*, was 0.656 which indicates a strong correlation according to Haden's threshold of 0.6 [24, Table 5.1]. A graphical representation of the linear regression is presented below in Figure 4.

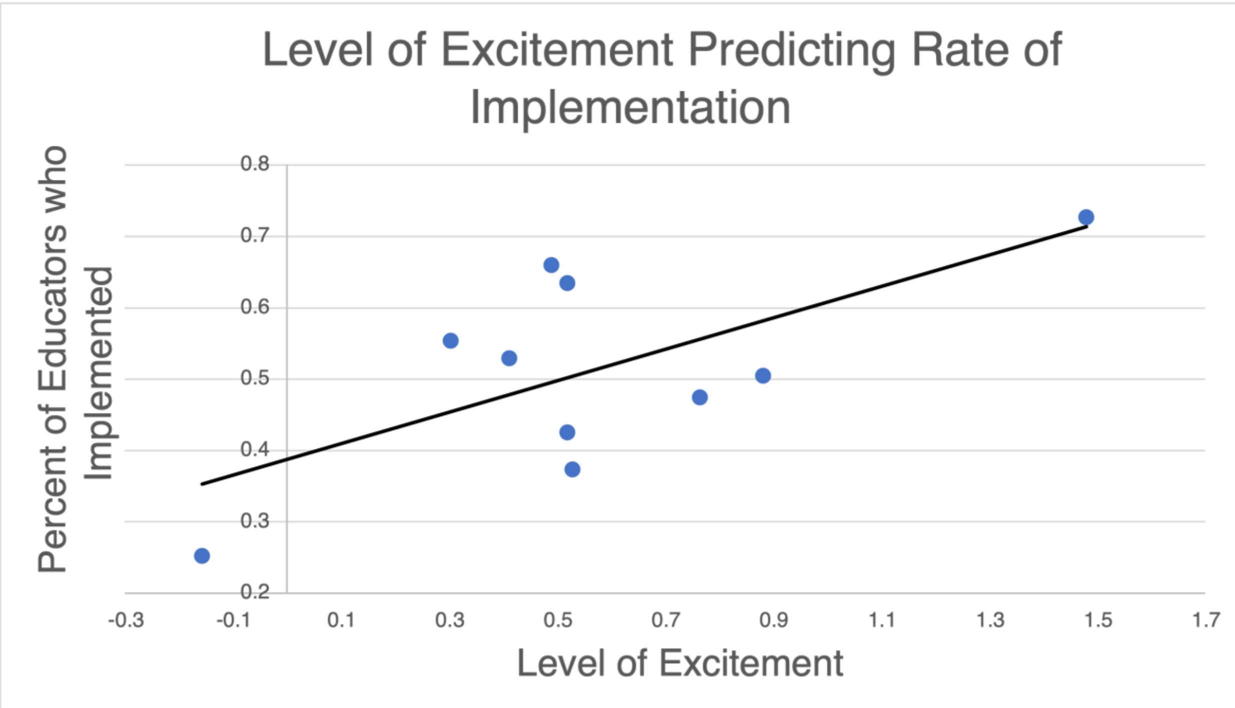

Figure 4: Linear Regression showing correlation between level of educator excitement about an intervention and percent of educators who implemented an intervention

As we found statistical significance and a strong correlation, we conclude that the average level of educator excitement about an intervention can predict the percent of educators who have implemented that teaching intervention. As this is a correlation, we cannot claim that educator excitement *directly causes* intervention adoption, but it seems reasonable to claim that educator excitement appears to be a significant factor in getting an intervention implemented.

RQ3: Do certain aspects of teachers make them more or less likely to adopt evidence-based teaching interventions?

In Table 7, we summarize the findings of the series of Welch's t-tests, or unequal variances t-tests which explore whether educator characteristics influence their tendency to adopt evidence-based teaching interventions. The educator characteristics are represented as rows, and the dependent variables which indicate the likelihood of implementation or directly measure implementation are represented as columns.

Each interior cell of the table represents a t-test we ran and contains the test statistic, *t*, the *p-value*, and the effect size or Hedge's g. As explained above, the corrected alpha value, due to repeated testing on dependent variables, is .017. None of the tests yielded significant results, and many of the reported effect sizes were weak.

Table 7: Summary of Welch's t-tests exploring whether educator characteristics influence intervention adoption

Educator Characteristics	**Excitement**	**Implementation**	**Future Implementation**
Teaching CS Only vs Teaching non-CS	t = 0.75997 p = 0.45099 g = 0.17642	t = 0.5975 p = 0.55272 g = 0.13292	t = 1.73898 p = 0.08717 g = 0.36558
Industry vs Teaching	t = 1.30089 p = 0.20354 g = 0.35812	t = 0.15779 p = 0.87543 g = 0.03531	t = -0.81037 p = 0.42336 g = 0.19770
Teaching vs Research Institution	t = 0.32601 p = 0.74512 g = 0.06479	t = -0.02833 p = 0.97746 g = 0.00571	t = -0.34225 p = 0.73291 g = 0.06872

These results indicate that educator factors such as having taught non-CS courses, amount of time spent in industry, and the type of institution they are employed at does not appear to affect whether educators are more or less likely to adopt evidence-based teaching interventions.

Discussion and Implications

In this section, we review our research questions one last time to tie our findings back to the literature and our proposed response hierarchy model.

RQ1: How does peer-reviewed research affect the adoption of teaching interventions?

Our findings to RQ1 built on the existing literature in a number of ways. First, we reproduced the self-reported finding from Barker *et al.* [3] that "Despite being researchers themselves, the CS faculty we spoke to ... did not believe that results from educational studies were credible reasons to try out teaching practices." Our analysis yielded no meaningful differences between the group presented with research-based descriptions versus the groups presented with plain descriptions. We also corroborated the results of Hovey *et al.* [4] that despite not being swayed by the results of educational research studies, many faculty learn about teaching interventions by going to computer science education conferences, or in our case, by reading their proceedings.

One interesting tension in this with past literature is that Hovey *et al.* [4] also noted that faculty were more motivated to adopt an intervention because it was framed as a way to reduce the underrepresentation of women and minorities from pursuing CS degrees. Given this is generally a finding from an educational research study, it warrants further investigation if CS faculty find educational studies so un-credible to the point that they are more willing to believe a peer's framing over a research result.

Turning to our model, our findings that peer-reviewed conference proceedings predict awareness upholds our theory that we can consider at least the first part of the intervention process similar to a marketing-inspired response hierarchy model. Future work can explore what other analogies can be drawn from the business world to inform the variety and level of effectiveness of different methods for getting the word out about teaching interventions. For example, there are whole firms and subsections of the marketing industry devoted to making your website higher on the search results page and designing your web pages so as to clearly and effectively convey information. Given the prevalence of research project webpages, there may be an opportunity to learn basic practices to get our work discovered by other educators.

RQ2: Which real/perceived benefits and challenges of teaching interventions are most convincing/influential in intervention adoption decisions?

Our findings to RQ2 built on the finding of Ni [10] that educator excitement is a positive factor in facilitating adoption. First, we showed that the combination of perceived benefits and challenges of an intervention can explain educator excitement. We then reproduced the finding that educator excitement predicted intervention adoption. Notably, instead of doing this at a more general level (as we did in our previous work), we showed that educator excitement can be leveraged at the fine-grained level of a specific, single intervention.

Similarly, our finding that the most influential benefits across interventions were improved student understanding, increased student engagement, and increased preparation for future career, reproduced the findings of Hovey *et al.* who noted that "faculty who tried an innovation were motivated primarily by concerns for students' learning and course experience, including their engagement and participation" [4, p. 483]. However, our findings illustrated that challenges were more varied across both interventions and respondents. While Hovey *et al.* identified "lack of time, logistical issues, and satisfaction with their current teaching practices" as factors that reduced faculty willingness to try an innovation [4, p. 483], satisfaction with current teaching practices showed no significant influence, lack of time showed significance for only one intervention and aspects such as concern about tenure and being limited by a department set curriculum far out-weighed logistical issues.

Turning to our model, demystifying excitement as being composed of perceived benefits and challenges illustrates that Cognitive and Affective are highly interrelated and not sequential. This suggests that our modifications to the AIDA model, inspired by Montazeribarforoushi *et al.* [20], were well-founded. Similarly, educator excitement (Affective), which we have seen is based on perceived benefits and challenges (Cognitive), strongly predicts the adoption of interventions (Behavior). This helps support our theory that Behavior is a direct response to Affective and Cognitive Stages.

RQ3: Do certain aspects of teachers make them more or less likely to adopt evidence-based teaching interventions?

This final question does not build directly on CS education literature but offers an interesting finding -- educator factors such as having taught non-CS courses, amount of time spent in industry, and the type of institution they are employed at do not appear to affect whether educators are more or less likely to adopt evidence-based teaching interventions. With the wide variety of backgrounds CS faculty come from, finding that these differences do not appear to intrinsically hinder any faculty group from adopting evidence-based interventions is comforting.

Turning to our model, this lack of evidence that specific educator characteristics explain adoption decisions suggests that at least one of the most apparent confounding factors, suggested by the marketing literature, does not complicate our proposed model.

Conclusion

Our work builds on previously disparate research probing the black box of how CS faculty choose to adopt evidence-based interventions. First, we reproduced many of the previous self-reported findings using different methodologies. We also illustrate the refinement of their intervention-agnostic instruments to address specific teaching interventions and find intervention-specific differences in the results. Finally, we tie together these previously disparate findings by proposing a cohesive model of how faculty adopt interventions, demystifying what happens between a faculty member learning about an intervention and successfully adopting the intervention.

Our results suggest that our proposed simplified response hierarchy model holds explanatory power for illustrating how faculty members become aware of and choose to adopt evidence-based teaching interventions. Finding that the number of publications predicts awareness upholds our theory that we can consider at least the first part of the intervention process similar to a response hierarchy model, bolstering our proposal of a marketing-inspired model. Our specifically proposed model is supported in two ways. First, our illustration of excitement being composed of perceived benefits and challenges illustrates that Cognitive and Affective are highly interrelated and not sequential. Second, educator excitement, based on the difference between benefits and challenges, strongly predicting adoption, helps support our theory that Behavior is a direct response to Affective and Cognitive Stages. Finally, our lack of findings when exploring educator characteristics helps assuage concerns about missing aspects of our model. This offers new insights and avenues of exploration into how to effectively disseminate research results, increasing the likelihood that the associated teaching interventions are adopted.

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